STREAMFLOW MODELING OF A LARGE ARID CATCHMENT USING SEMI-DISTRIBUTED HYDROLOGICAL MODEL AND MODULAR NEURAL NETWORK

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ABSTRACT

Calibration and validation of hydrological models for simulating stream flow can usually be a promising procedure for future sustainable watershed development. Therefore, development of hydrological models with attributed capabilities is vital to explore the models. Recently, arid climate regions are facing critical water resource problems due to elevated water scarcity. The main objective of this research is to compare the Soil and Water Assessment Tool (SWAT), a knowledge driven by semi-distributed hydrological model, with the Modular Neural Network (MNN), a data driven technique, in predicting the daily flow in arid and large scale. Development of SWAT required digital elevation map, hydro-meteorological data, land use map, and soil maps; whilst, the MNN only needed hydro-meteorological data. For both models, a sensitivity analysis that included both calibration and validation with individual uncertainty evaluation methods was carried out. Generally, results for relative errors such as Nash-Sutcliffe, coefficient of determination and percent of bias favored the SWAT for the validation period. Not only that, the absolute error criteria such as root mean square error, mean square error and mean relative error obtained were close to zero for the SWAT as well within the same period. The mean absolute error for both models was similar during the validation period. Results of the uncertainty evaluation were in satisfactory range. Both models had given similar trend for flow prediction during the validation period. Results of box plot, according to 50% (median) of daily flow, showed that both models had respectively overestimated (MNN) and underestimated (SWAT) the daily flow during validation period. Evaluation on runoff volume for each year showed that both models had a one-year underestimation and three-year overestimation in the same period. However, the overestimation of MNN was more obvious. As a conclusion, this study showed that both models have promising prediction performance for daily flow in a large scale watershed with arid climate.

ABSTRAK

Kalibrasi dan validasi model hidrologi untuk simulasi aliran sungai biasanya boleh menjadi prosedur yang paling sesuai untuk pembangunan kawasan tadah air lestari di masa depan. Oleh itu, pembangunan model-model hidrologi yang berkebolehupayaannya adalah penting untuk meneroka model-model berkenaan. Baru-baru ini, kawasan beriklim kering sedang menghadapi masalah kekurangan air yang semakin kritikal. Objektif utama penyelidikan ini adalah untuk membanding satu kaedah penilaian air dan tanah (SWAT), iaitu satu model hidrologi separa-teragih berdasarkan penggunaan segala maklumat legeh, dengan satu rangkaian neural modular (MNN), iaitu satu teknik penggunaan data untuk ramalan aliran harian dalam kawasan kering dan luas. Pembangunan SWAT memerlukan peta digital aras ketinggian, data hidro-meteorologi, peta digital -guna tanah dan peta tanah-tanih; sementara MNN hanya memerlukan data hidro-meteorologi. Analisis sensitif, kalibrasi dan validasi, dan analisis ketidaktentuan telah dilaksanakan untuk kedua-dua model dengan kaedah masing-masing. Secara amnya, keputusan ralat relatif seperti Nash-Sutcliffe, pekali penentuan dan peratus kecenderungan menyebelahi SWAT dalam waktu validasi. Kriteria ralat yang lain seperti ralat minimum punca kuasa dua, ralat purata kuasa dua dan ralat purata relatif yang diperolehi juga telah menghampiri nilai sifar untuk SWAT pada waktu yang sama. Ralat mutlak purata untuk kedua-dua model menunjukkan kebolehupayaan yang sama semasa waktu validasi. Keputusan analisis ketidaktentuan adalah dalam julat yang memuaskan. Kedua-dua model telah menghasilkan tahap kecenderungan yang sama untuk peramalan aliran dalam waktu validasi. Keputusan (box plot) berdasarkan 50%(median) aliran harian menunjukkan bahawa kedua-dua model telah masing-masing terlebih anggaran (MNN) dan terkurang anggaran (SWAT) aliran seharian dalam waktu validasi. Anggaran isipadu air larian untuk setiap tahun menunjukkan bahawa kedua-dua model telah masing-masing memberikan satu tahun terkurang anggaran dan tiga tahun terlebih anggaran dalam waktu yang sama. Terlebih anggaran dalam tahun yang sama oleh MNN adalah lebih jelas. Kesimpulannya, kajian ini telah menunjukkan kemampuan yang meyakinkan untuk peramalan aliran harian dalam kawasan tadahan yang sangat luas dan beriklim kering bagi kedua-dua model.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLES

Alpha_Bf	-	Base flow alfa factor (days)
ANFIZ	-	Adaptive neuron fuzzy inference system
ANN	-	Artificial Neural Network
Biomix	-	Biological mixing efficiency
Blai	-	Maximum potential leaf area index
BPA	-	Back propagation algorithm
BPMA	-	Back propagation with momentum algorithm
bsn	-	Basin files
Canmx	-	Maximum canopy storage (mm)
CGA	-	Conjugate Gradient Algorithm
CGCM	-	Canadian Global Coupled Model
Ch_K2	-	Effective hydraulic conductivity in main channel (mm/hr)
Ch_N2	-	Manning's "n" value for the main channel
CLAY	-	Clay content
CMS	-	Cubic meter per second
CN	-	Curve number
Cn2	-	Initial SCS runoff curve number for moisture condition II
CRIR	-	Agricultural area
CUP	-	Calibration and uncertainty procedures
DEM	-	Digital elevation map
div	-	Volume of water added or removed from the reach for the day through diversions (m^3)
EPCO	-	Plant uptake compensation factor
ESCO	-	Soil evaporation compensation factor
EVRCH.bsn	-	Reach evaporation coefficient
Ext	-	SWAT file extension
FAO	-	Food and agriculture organization
FFNN	-	Feed Forward Neural Networks
GA	-	Genetic Algorithm
GB	-	Giga bites

GFF	-	Generalized Feed Forward
GHz	-	Giga hertz
GIS	-	Geographic Information System
GLUE	-	Generalized Likelihood Uncertainty Estimation
GRU	-	Grouped Response Unit
gw	-	Ground water files
Gw_Delay	-	Groundwater delay time (days)
Gwqmn	-	Threshold depth of water in the shallow aquifer (mm)
Gw_Revap	-	Groundwater "revap" coefficient
HRU	-	Hydrological Response Unit
HRU-FR	-	Hydrological response unit fraction
hh:mm	-	Hour-Minute
hr	-	Hour
Hydrogrp	-	Soil hydrological group
HYMO	-	Hydrologic Model
i	-	Intensity of precipitation
IM	-	Inverse model
IRIMO	-	Meteorological Organization of Iran
j	-	Input Neuron
k	-	Hidden neroun
k	-	Number of observed data
km^2	-	Square Kilometer
l	-	Output neuron
L	-	Channel length (km)
LH-OAT	-	Latin hypercube sampling by one at a time design
LMA	-	Levenberg-Marquardt algorithm
Lup.file	-	Land use update file
M	-	Total number of observations
m	-	Parameters
MAE	-	Mean Absolute Error
Max Temp	-	Average daily maximum temperature
mgt	-	Management file
MIGS	-	Mix grassland/shrub land
Min Temp	-	Average daily minimum temperature

MLP	-	Multilayer Perceptron
MLR	-	Multiple linear regression
MNN	-	Modular Neural Network
MNN1..14	-	Developed MNN architectures number
MRE	-	Mean Relative Error
M-RBF-NN	-	Modular Radial Basis Function Neural Network
MSE	-	Mean Squared Error
N	-	Number of interval
n	-	Total number of observations
n	-	Number of time steps
n	-	Total number of measured data
n	-	Iteration
n	-	Number of lags
NRCS-CN	-	Natural Resources Conservation Services Curve Number
N S	-	Nash-Sutcliffe
ORCD	-	Orchard
Paraname	-	Name of parameter in SWAT
ParaSol	-	Parameter Solution
PBIAS	-	Percentage of bias
PCP	-	Precipitation (mm)
PCPD	-	Average number of days of precipitation in month
PCPMM	-	Average total monthly precipitation (mm)
PCPSKW	-	Skew coefficient for daily precipitation in month
PCPSTD	-	Standard deviation for daily precipitation in month (mm/day)
PE	-	Process Element
PET	-	Potential Evapotranspiration (mm/day)
PLS	-	Partial Least Square
PPU	-	Percent Prediction Uncertainty
PR_W(1)	-	Probability of a wet day following a dry day in the month
PR_W(2)	-	Probability of a wet day following a wet day in the month
PU	-	Predictive uncertainty index
Q	-	Discharge (m^3/s)
r	-	Parameter value is multiplied by (1 + a given value) or relative change

RAINHHMX	-	Maximum 0.5 hour rainfall in entire period of record for Month
RAM	-	Random access memory
RBF	-	Radial Basis Function Network
RCHRG_DP	-	Ground water recharge to deep aquifer
REA	-	Representative Elementary Area
Revapmn	-	Threshold depth of water in the shallow aquifer for percolation to the deep aquifer (mm)
RMSE	-	Root Mean Square Error
ROCK	-	Rock fragment content
ROTO	-	Routing outputs to outlet
rte	-	Routing files
RR	-	Rainfall-Runoff
S	-	Retention parameter (mm)
SAND	-	Sand content
SCS-CN	-	Natural Resources Conservation Service Curve Number Method
SEE	-	Unbiased standard error
Sftmp	-	Snowfall temperature (ºC)
SHRB	-	Shrub land
SILT	-	Silt content
Slsubbsn	-	Average slope length (m)
Slope	-	Average slope steepness (m/m)
Smfmn	-	Melt factor for snow on December 21 (mm /ºC-day).
Smfmx	-	Melt factor for snow on June 21 (mm /ºC-day).
SMMN	-	Spiking Modular Neural Networks
Smtmp	-	Snow melt base temperature (ºC).
SOFM	-	Self Organize Feature Map Network
sol	-	Soil files
soltext	-	Soil texture
Sol_Alb	-	Moist soil albedo
SOL_AWC	-	Available water capacity of the soil layer (mm/mm)
SOL_BD	-	Moist bulk density (g/cm^3)
SOL_CBN	-	Organic carbon content (% soil weight)
SOL_CRK	-	Potential or maximum crack volume of the soil profile (m^3/m^3)
SOL_EC	-	Electrical conductivity(ds/m)

SOL_K	-	Saturated hydraulic conductivity (mm/hr)
Sol_Z	-	Depth from soil surface to bottom of layer (cm)
SOM	-	Self-organizing map
SSA	-	Singular Spectrum Analysis
STD	-	Standard deviation of observed values
subbsn	-	Sub-basin number
SUFI-2	-	Sequential Uncertainty Fitting-2
Surlag	-	Surface runoff lag coefficient
SVM	-	Support Vector Machine Network
SW	-	Soil water content of the entire profile excluding the amount of water held in the profile at wilting point (mm)
SWAT	-	Soil and Water Assessment Tool
Tanh	-	Tangent hyperbolic
Temp	-	Average daily temperature (^{0}C)
Timp	-	Snow pack temperature lag factor
Tlaps	-	Temperature lapse rate (ºC/km)
tloss	-	Volume of water lost from the reach by transmission through the bed (m^3)
TMP	-	Temperature (^{0}C)
TMPMN	-	Average daily minimum air temperature for month (ºC)
TMPMX	-	Average daily maximum air temperature for month (ºC)
TMPSTDMN	-	Standard deviation for daily minimum air temperature in month (ºC)
TMPSTDMX	-	Standard deviation for daily maximum air temperature in month (ºC)
TT	-	Travel time (hour)
t	-	Time (days)
t-1,t-2,…(t-n)	-	One day before present day
USDA-ARS	-	US Department of Agriculture, Agricultural Research Service
USLE_K	-	USLE equation soil erosion factor (K)
URLD	-	Residential- low density
URMD	-	Residential-medium density
v	-	Parameter value is replaced by given value or absolute change
W	-	Channel width at water level (m)

W(n)	-	Weight (free parameter)
WGN	-	Weather Generator File
x	-	Type of adjustment parameter in SWAT
X(n)	-	Input variable
α	-	Momentum
η	-	Step size
ν	-	Degrees of freedom
λ	-	Latent heat of vaporization (MJ kg^{-1})
β	-	Line Slope
σ_X	-	Standard deviation of the measured variable
v_{ov}	-	The overland flow velocity (m/s)
δ_i(n)	-	Local error
ΔV_{stored}	-	Volume of storage (m^3)
R^2	-	Coefficient of determination
Y^{obs}	-	Measured values at time step i
Y^{sim}	-	Measured values at time step i
a_x	-	Regression intercept for a channel
α_{tc}	-	Fraction of daily rainfall that occurs during the time of concentration
b_k	-	Bias of the hidden layer
b_l	-	Bias of the output layer
b_x	-	Regression slope for a channel
bnk_{in}	-	Amount of water entering bank storage (m^3)
$coef_{ev}$	-	Evaporation coefficient
CN_1	-	Moisture condition I
CN_2	-	Moisture condition II
CN_3	-	Moisture condition III
$D_i\,(n)$	-	Desired response to observed out put
d_x	-	Average distance between the upper and the lower 95PPU
E_a	-	The amount of evapotranspiration on day i (mm)
E_{ch}	-	The evaporation from the reach for the day (m^3)
$E_i\,(n)$	-	Error system
E_o	-	Potential evapotranspiration (mm d^{-1})
$E_{Relative}$	-	Relative Error

$fr_{\Delta t}$	-	Fraction of the time step in which water is flowing in the channel
fr_{trns}	-	Fraction of transmission losses partitioned to the deep aquifer
H_0	-	Extraterrestrial radiation (MJ m^{-2} d^{-1})
I_a	-	Initial abstractions (mm)
K_{ch}	-	Effectiveness of hydraulic conductivity for channel alluvium (mm/hr)
L_{ch}	-	Channel length (m)
L_{slp}	-	Sub-basin slope length (m)
O_i	-	Measured value at time i
P_{ch}	-	The wetted perimeter (m)
P_i	-	Estimated value at time i
P_{max}	-	Maximum observed data
P_{min}	-	Minimum observed data
P_n	-	Scaled data
P_o	-	Observed data
PCP_t	-	Precipitation (mm) with attributed lags (day)
Q_{avg}	-	Average observed stream flow
Q_{gw}	-	Amount of return flow on day i (mm)
Q_o	-	Observed value of flow
Q_{obs}	-	Observed value at time i
Q_{obsavg}	-	Average of observed values
q_{out}	-	Discharge rate (m^3/s)
Q_p	-	Predicted value of flow
q_{peak}	-	Peak runoff rate (m^3 s^{-1})
Q_{sim}	-	Predicted value at time i
Q_{simavg}	-	Average of predicted values $Q_{stor,i-1}$- Surface flow lagged from the previous day (mm)
$Q_{stor,i-1}$	-	Surface flow lagged from the previous day (mm)
Q_{surf}	-	The amount of surface runoff on day i (mm)
Q_{surf}	-	Accumulated runoff excess (mm)
Q'_{surf}	-	Amount of surface flow created in the sub basin on a given day (mm)
Q_t	-	Discharge (m^3/s) with attributed day lags

$Q_{(m.,Obs)i}$	-	Maximum values of the actual discharge during **i** time
$Q_{(m.,Sim)i}$	-	Maximum values of simulated discharge during **i** time
R_{day}	-	Rainfall depth for the day (mm)
R_{tc}	-	Amount of precipitation during the time of concentration (mm)
S_{max}	-	The maximum value the retention parameter (mm)
SW_t	-	Final soil water content (mm)
SW_0	-	Initial soil water content on day i (mm)
T_{av}	-	Mean air temperature for a given day(°C).
t_{ov}	-	Time of concentration for overland flow (hr)
t_{ch}	-	Time of concentration for channel flow (hr)
t_{conc}	-	Time of concentration(hour)
t_{loss}	-	Transmission losses of channel (m^3)
T_{mn}	-	Minimum air temperature for a given day (°C)
T_{mx}	-	Maximum air temperature for a given day (°C)
V_{bnk}	-	The volume of water summed to the river using return flow from bank storage (m^3)
V_{in}	-	The volume of water flowing into the reach during the time step (m^3)
V_{in}	-	Volume of inflow (m^3)
V_{out}	-	Volume of water flowing out of the reach (m^3)
V_{out}	-	Volume of outflow (m^3)
$vol_{Qsurf,f}$	-	Volume of runoff after transmission losses (m^3)
$vol_{Qsurf,i}$	-	Volume of runoff prior to transmission losses (m^3)
V_{stored}	-	Storage volume (m3)
$V_{stored,2}$	-	Volume of water in the river at the end of the time step (m^3)
$V_{stored,1}$	-	Volume of water in the reach at the beginning of the time step (m^3)
vol_{thr}	-	Threshold volume for a channel(m^3)
W_i	-	Bias vector
W_{kj}	-	Weight of the j^{th} input neuron and k^{th} hidden neuron
W_{lk}	-	Weight between the k^{th} hidden neuron and l^{th} output neuron
w_{seep}	-	The amount of water entering the vadose zone
W_1, W_2	-	Shape coefficients

$X_i^{lin} = \beta x_i$	-	Scaled and offset activity inherited from the Linear
X_{min}	-	Minimum input range
X_{max}	-	Maximum input range
X_n	-	Normalized inputs
X_L	-	2.5^{th} percentiles of the cumulative distribution for each simulated data
X_r	-	Original inputs
X_U	-	97.5th percentiles of the cumulative distribution for each simulated data
$Y_i(n)$	-	Observed out put

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

A hydrologist or water resources project manager/planner may be interested in knowing the total amount of runoff for a watershed during a specified period of time. The reason can be to obtain reliable runoff yield at a catchment to have more confident on the design-attributed parameters such as the storage capacity, height, power generation, release pattern for irrigation, municipal demands and other requirement (Patra, 2008). Recently, runoff prediction has become significant in regions with arid and dry climates. As such, the management, assessment and planning of water resources are important issues in human development, especially in such regions where rainfall and groundwater supply are limited. McIntyre et al. (2009) has reported that there is a serious need to develop our cognition ability in predicting the hydrological responses in arid catchments.

Arid hydrology has recently become an important topic to water resource planners and researches serious in seeking for solutions in arid zones suffering from water resources crisis. Iran, especially the arid southern part of Iran as well as other Middle East countries, have been facing aridity problems. Reports and investigations showed that Iran have suffered from water crisis since 1999, which then pushed the Iranian government to accept foreign aid (Foltz, 2002). Therefore, development of new techniques such as watershed modeling can be helpful to the cognitive management of water resource management and sustainability for future development.

Runoff is one of the controversial and basic parameter in hydrology that has a significant role in a catchment (Alizadeh, 2007). An efficient design of water structures and sustainable development firstly involve a reliable stream flow prediction from the contributing catchment area. The amount of runoff can be derived from a given precipitation, initial moisture, land use, slopes of the catchment, intensity, distribution, and duration of the rainfall (Irawan, 2005). Hence, rainfall-runoff relationship prediction is inevitably a complicated and non-linear procedure (Shakir and Shardra, 2008).

In the 1960s and 1970s, the use of digital computers for hydrological sciences has overcome some complicated computation problems for rainfall-runoff predictions. For instance, the first watershed model was the Stanford Watershed Model, developed in 1966 by Crawford and Linsley (Singh, 1995). Subsequently, another potentially efficient modeling tool was introduced, and has since been widely used in the soil and water management field. Essentially, rainfall-runoff models are important tools for water resource planning, development, and management (Tombul and Ogul, 2006). The principal techniques of hydrological modeling are made up of the two powerful facilities of the digital computer, which are: (i) the ability to carry out vast numbers of iterative calculations, and (ii) the ability to answer 'yes' or 'no' to specifically designed interrogations (Shaw,1994). These days, development/application of hydrological models is a controversial topic due to the prediction of hydrological processes (Singh et al., 2012). Nevertheless, the development of different types of hydrological models in recent days is mainly done based on a review on the weaknesses and strengths of these models. One of the important subjects concerns stream flow modeling and is attributed to the discussions on the assessment of predicted peak flows, the capability of the runoff volume prediction, and so on. Therefore, this research is geared towards the evaluation of stream flow modeling by using the attributed and available data in hydro-meteorology, geomorphologic, agricultural and pedology. Two hydrologic models were used in this research, namely semi-distributed hydrological model (Soil and Water Assessment Tool (SWAT)) and modular neural network (MNN) model.

SWAT was developed by the US Department of Agriculture, Agricultural Research Service (USDA-ARS). It is a semi-distributed hydrological model with some major components like surface hydrology, weather, sedimentation, soil temperature, crop growth, nutrients, groundwater, and lateral flow. SWAT is one of the models which can be developed in large scale and un-gauged basins (Xu et al., 2009a). The reason of developing SWAT model is to delineate a catchment of any sizes, especially in large scale. Its scientific association also concerns its application under different environment.

The black-box/data driven techniques describe the relationship between the input (precipitation) and the output (runoff) mathematically. This hydrological model simulates hydrological process without describing or understanding the physical process. Artificial neural networks (ANNs) have been introduced as a black box/data driven models, while modular neural networks are one of the sub-classes of artificial neural networks (Wu and Chau, 2011). The idea of black box/data driven models is based on the estimation of an output by a function from the input, which is similar to the process of biological neuron cell in the brain. Development of modular neural networks, which are sometimes taken as a hybrid model, is gaining popularity for developing rainfall-runoff relationships (Zhang and Govindaraju, 2000), hydrological processes (Parasuraman et al., 2006), and ground water studies (Almasri and Kaluarachchi, 2005). As a summary, modular networks are still in the stage of infancy. Therefore, there is still a need to evaluate modular networks in terms of its development and generalization for hydrological processes. Essentially, its low data collection cost and fast calculation as a sub-class of artificial neural networks can be the two logical reasons for it to become popular among hydrologists.

In this study, the Roodan watershed in the Southern part of Iran has been selected as the study area. The Roodan watershed is one of the largest catchments which is around 10570km^2. It has the potential for future agriculture, animal husbandry and sustainable tourism activities. With respect to modeling, no SWAT model has been developed for this watershed, and so does the MNN for daily stream flow prediction. The comparison of semi-distributed hydrological model (SWAT) and neural network (MNN) in arid and large catchment can be important for the assessment and discussion on their abilities, and their advantages and disadvantages for stream flow modeling.

1.2 Statement of Problem

The statements of problems which have been identified in this research are as follows:

a) With reference to Parida et al. (2006), prediction on rainfall-runoff relationships has become more difficult for an arid catchment due to the complexity involved in the process of transformation from rainfall to runoff. Sen, (2008) reported that arid regions require more surveys because of a shortage in literatures and cognition modeling responses. In recent years, arid regions have suffered from many problems such as water crisis and depletion of underground waters (Al-Damkhi et al., 2009; Kanae, 2009). Therefore, there is a need to model hydrological processes for arid regions for better cognition of complex rainfall-runoff relationships.

b) The major difficulty in the development of hydrological models is the different concepts of these models. The semi-distributed hydrological model (e.g., SWAT) can be a physically-based model which deal with physical concept of catchment. In contrast, a modular network model is a black box/data driven model which only seeks for best generalization of mathematical procedures. Moreover, development of hydrological models is influenced by the complexity of hydrological processes and this issue is more significant for large scale catchments. Therefore, it is necessary to find the advantages and disadvantages of the semi-distributed hydrological model and the black box /data-driven model (e.g., SWAT versus MNN). By applying SWAT and MNN in the same region, it can help in visualizing and identifying the weaknesses and strengths of these two different models.

c) A semi-distributed hydrological model such as SWAT requires large number of input parameters for its calibration. Generally, the parameters adjusted for calibration are not measured openly in the case study. SWAT model is usually calibrated manually by using the trial-and-error procedure to make a comparison with the data-driven models. Manual calibration provides proficiency by allowing the modeler to have prior knowledge of the catchment being simulated. Clearly, hydrological models such as SWAT require tough manual effort to obtain better results and it is more time-consuming due to the adjustment needed for a large number of parameters. Sometimes, the complicated calibration process may cause uncertainties in the results due to the nature of the model. This concept is increasingly significant for SWAT model (Abbaspour et al., 2009, 2007). As a result, SWAT requires an optimum calibration and uncertainty procedure to allow a comparison with data driven models like MNN. Therefore, there is a need for SWAT calibration using efficient approach to get optimum results. In this study, the sequential uncertainty fitting-2 (SUFI-2) has been integrated for the calibration of SWAT model.

d) An accurate prediction of rainfall-runoff relationship is extremely difficult due to the spatial and temporal variability of watershed characteristics as well as an incomplete understanding of the underlying complex physical processes (Srivastava et al., 2006). In regard to this, the modular neural networks have found another technique for different hydrology subjects (Almasri and Kaluarachchi, 2005). The motivation of modular (hybrid) architecture in rainfall-runoff modeling came from Zhang and Govindaraju, (2000). In general, modularity architectures allow the hydrologist to carry out high order accounting to have more options in solving complex pattern recognition. This is a motivation to the development of modular networks models. Two major difficulties of the development of neural networks such as MNN are overtraining and over parameterization, which have significant roles on the strength of optimum generalization (test). Therefore, there is a need for integrating cross validation technique (early stopping) to avoid overtraining and predictive uncertainty index (PU) to prevent over parameterization of neural networks.

In conclusion, the comparisons and evaluations of SWAT and MNN can be a promising effort in the arid Roodan watershed to explore the capabilities of related models. The development of the aforementioned models offers a fair cognition for the complex rainfall-runoff relations in large scale arid regions.

1.3 Justification and Significance of Research

Water scarcity affects the agriculture and food production (Kanae, 2009). Global warming has been proven to decrease the water availability in arid and semi-arid regions, where major crop are cultivated. The decreasing water supply for agriculture and domestic usage will inevitably threaten arid and semi-arid areas. Oki and Kanae, (2006) has previously showed their geographical distribution of the ratio between water withdrawal and water availability, and this is as presented in Figure 1.1 (the red coloring indicates a high ratio of water scarcity). Alizadeh, (2007) stated that in the coming years, Iran will be a water-stressed country.

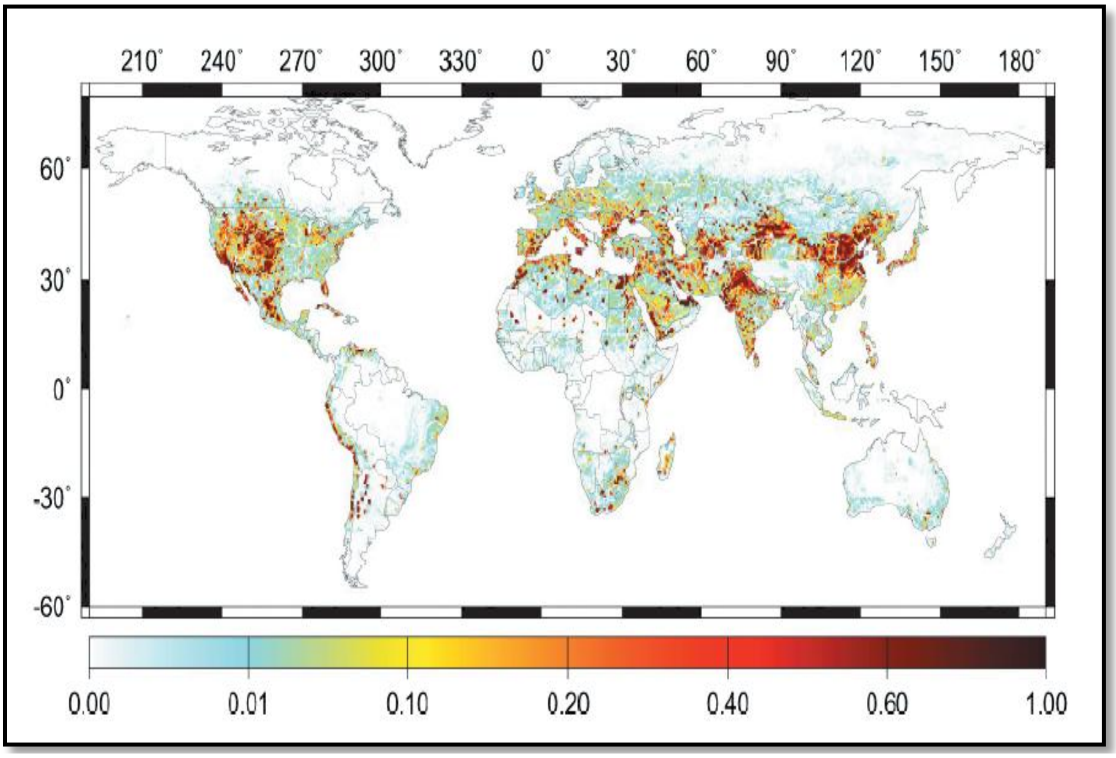

Figure 1.1 Global distribution of water scarcity (i.e., the ratio between water withdrawal and water availability at each cell of map) by Oki and Kanae, (2006)

By virtue of Rezaitavabeh et al. (2007), one of the logical solutions for water resource management and promotion of sustainable catchment is to invest in the harvest and collection of surface water. To date, watershed models have become a main tool in addressing a wide spectrum of environment and water resource problems (Singh and Frevert, 2006). Thompson et al. (2004) cited that modeling is fast and less expensive for the evaluation of different management strategies, and thus, can help to avoid undesirable outcomes. Until now, researchers are still persisting on testing and evaluating the stream flow modeling via new techniques to improve the models' efficiency and to explore the pros and cons of these hydrological models.

In terms of hydrology, researchers are now trying to find the advantages and disadvantages of hydrological modeling to optimize the prediction of rainfall-runoff relationships. This is to find out the capability of the models for future studies (Norani et al, 2008). This function gets more important when different types of hydrological models with various concepts have been established. Therefore, it is essential to identify their strengths and weaknesses. With reference to Boughton (1984), due to the sparseness of hydrological data in arid and semi-arid areas, the values vary in the results of every hydrological investigation done in these regions. Iran suffers from shortage of water because of the arid and semi-arid climatic conditions, and the country only has an average annual rainfall of 250 mm, which is only around one-third of the world's average rainfall. Nevertheless, this region has the potential to be developed for agricultural purposes and for collecting surface water. Therefore, the development of hydrological models with different concept such as SWAT and MNN can assist in the daily flow prediction for the Roodan region.

In conclusion, this research is significant for the development of the most popular models (SWAT and MNN) using different types of data in arid region. This research focuses on the prediction of daily runoff. The development of SWAT and MNN can assist in the daily stream flow prediction for the Roodan watershed. Also, daily flow prediction is important for optimal management of the availability of water resources in every basin. A comparison between SWAT and MNN can be an opportunity for the evaluation of optimum solutions by modeling the stream flow for future planning and investment efforts. Finally, this project can show the behavior of SWAT and MNN models, as a subsidiary tool for hydrologists, in predicting daily stream flow in large arid region. Last but not least, such study in arid regions can be interesting and valuable since it has substantially different features in comparison with other climates, as reported by Sen, (2008).

1.4 Study Objectives

The aim of this study is to make a comparison on the daily stream flow prediction between the semi-distributed hydrological model, i.e., the soil and water assessment tool (SWAT), and the black-box/data driven model, i.e., modular neural network (MNN). The objectives of this study are as follows:

1. To model the daily rainfall-runoff relationship of a large arid watershed;
2. To calibrate the SWAT based on the sequential uncertainty fitting-2 algorithm;
3. To propose a MMN using cross-validation technique for modeling the rainfall-runoff relationship; and
4. To evaluate the performance of SWAT and MNN in large arid climate.

1.5 Scope of the Study

The present study was undertaken to compare the daily stream flow through two kinds of hydrological models - SWAT and MNN. The scope of this research can be divided into three parts. The first part involves the development of SWAT model for daily stream flow simulation. The required data for SWAT are the digital elevation modeling map (DEM), the hydro-meteorological data (take from year 1988 to 2008), and the soil and land cover maps collected by individual features availability. A sensitivity analysis and a calibration and uncertainty procedure have been employed together with the application of the Latin hypercube sampling by one at a time design (LH-OAT). These are embedded in SWAT version 2009 and the SUFI-2 algorithm can be found in the SWAT-CUP program (version 2009), respectively. Finally, the weaknesses and strengths of the SWAT model are observed and interpreted for the prediction of daily runoff in the large yet arid Roodan watershed in the southern part of Iran.

The second part of this research involves the development of MNN with two modules (neural expert) for rainfall-runoff relationships in Roodan watershed using the hydro-meteorological data from year 1988 to 2008. Such development requires the training with cross validation and test. Basically, a heuristic method has been involved to find the optimum architecture and attributed components such as number of cells, hidden layers, input variables, and coefficients related to the step size and momentum terms. This study includes the evaluation of uncertainty in the MMN using the predictive uncertainty (PU) index.

The third part of this research involves the respective evaluations and comparisons between the daily flow models for the arid and large scale catchment area through general graphical and non-graphical analyses. This comparison has offered the general features of robustness, accuracy, efficiency, and reliability. This has made it possible to identify and discuss the advantages and disadvantages of SWAT versus MNN for daily flow prediction.

1.6 Structure of the Thesis

This thesis consists of five chapters. The first chapter presents the background, introduction, objectives, and the scope of this research. In the subsequent chapter, a review of relevant literature and theoretical definitions will be illustrated using the hydrological cycle. A discussion will also be put forth in regard to some water resource problems and crisis in arid regions, followed by an explanation on the runoff concept. Chapter 2 shall also introduce SWAT and MNN and other attributes of previous publications.

Chapter 3 shall introduce the Roodan watershed together with the analysis of usual data and the development of SWAT and MNN. Next, Chapter 4 shall explain the results obtained from the SWAT and MNN models before comparisons are made for the daily flow predicted by both models. These results were obtained from the sensitivity analysis, calibration and validation procedures, and the uncertainty analysis. Lastly, Chapter 5 shall conclude the present study and further suggests appropriate recommendations for future studies.

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